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ASYMPTOTIC SPECTRAL ANALYSIS OF CROSS-PRODUCT MATRICES  
(U) PRINCETON UNIV NJ DEPT OF STATISTICS G S WATSON

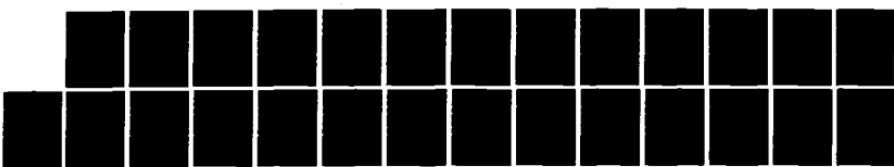
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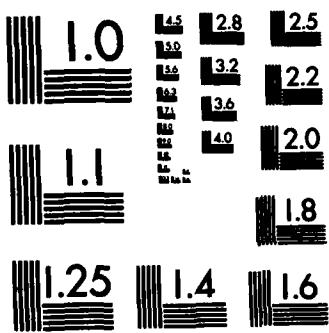
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## **ASYMPTOTIC SPECTRAL ANALYSIS OF CROSS-PRODUCT MATRICES**

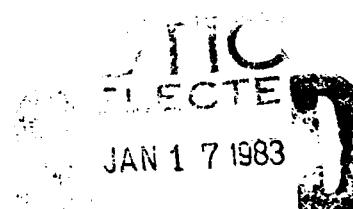
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# ASYMPTOTIC SPECTRAL ANALYSIS OF CROSS-PRODUCT MATRICES

by

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## ABSTRACT

Let  $x$  be a random vector in  $\mathbb{R}^q$  and  $M_n = n^{-1} \sum_1^n x_i x_i'$  be an estimator of  $M = E x x'$  with spectral form  $\sum_j \lambda_j P_j$ . An expository account is given of the estimation of  $\lambda_j$  and  $P_j$  from the eigenvalues and and vectors of  $M_n$  when  $n$  is large. This includes a derivation of the basic formulae using a complex variable method in the book by Kato (1980) and a contrasting matrix method. Several extensions are indicated.

# ASYMPTOTIC SPECTRAL ANALYSIS OF CROSS-PRODUCT MATRICES

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## 1. Introduction

T. W. Anderson (1963) derived the asymptotic distribution of the eigenvalues and vectors of the covariance matrix of a sample from a Gaussian distribution. Davis (1977) took his basic method and used it to get some results for the non-Gaussian case. The non-Gaussian case is of interest either because one wants to study the sensitivity of methods to deviations from Gaussianity - see e.g. Muirhead (1982) - or because one has to deal with other distributions. For example the distribution of the random vector might be entirely restricted to some manifold embedded in  $\mathbb{R}^q$  like the surface of the unit sphere or an hyperboloid of rotation; the cases of interest to us.

Kim (1978) at the suggestion of R. J. W. Beran, used results from the book by Kato (1976, 1980) on the perturbation theory of linear operators to find the asymptotic distribution of the eigenvalues of the matrix  $M_n = n^{-1} \sum_i x_i x_i'$  where the  $x_i$ 's are independently drawn from a certain distribution on the surface  $S_q$  of the unit sphere in  $\mathbb{R}^q$ . Tyler (1979, 1981) also used Kato's method to get results in classical multivariate analysis. But the technique is not well-known, nor immediately evident from Kato's book.

Kato's method calls upon Cauchy's Theorem in Complex Variable Theory. Specifically consider the integral of  $(z - z_0)^p$  anti-clockwise around a simple closed curve  $C$  in the complex plane which does not go through  $z_0$ .

$$\int_C (z - z_0)^p dz$$

where  $p$  is an integer. Unless  $p = -1$ , it is always zero. When  $p = -1$ , it is zero if  $z_0$  is outside  $C$  and  $2\pi i$  where  $z_0$  is inside  $C$ .

The techniques and formulae below have many possible applications. Some are given in Watson (1982a) but most remain to be exploited. In the next section Kato's method is explained for symmetric non-random matrices and then applied in Section 3 to covariance matrices.

The key formulae in Section 2 and the results of Section 3 have of course been obtained before by direct matrix methods -

- though they are hard to justify. The Kato method not only gives a better insight but is easier to do and to extend, e.g. to provide asymptotic expansions.

## 2. The key to Kato

If  $T_0$  and  $T_1$  are real symmetric  $q \times q$  matrices and  $x$  is a small real number

$$T(x) = T_0 + xT_1 \quad (2.1)$$

can be thought of as a linear perturbation of  $T_0$ . Let the spectral

representation of the matrix  $T_0$  be

$$T_0 = \sum_j \lambda_j P_j, \quad r \leq q \quad (2.2)$$

where

$$\left. \begin{array}{l} \lambda_1, \dots, \lambda_r \text{ are distinct real numbers,} \\ P_j' = P_j, \quad P_j P_k = \delta_{jk} P_j, \\ \text{rank } P_j = \text{trace } P_j = q_j, \quad \sum_j q_j = q \end{array} \right\} \quad (2.3)$$

Thus  $\lambda_j$  is an eigenvalue of  $T_0$  that is repeated  $q_j$  times. The invariant subspace  $V_j$  associated with  $\lambda_j$  has dimension  $q_j$  and  $P_j$  projects orthogonally onto  $V_j$  whose direct sum is  $\mathbb{R}^q$ .

The matrix  $T(x)$  may have  $q$  distinct eigenvalues but we would expect these to fall into  $r$  clusters about  $\lambda_1, \dots, \lambda_r$  and to condense on  $\lambda_1, \dots, \lambda_r$  as  $x \rightarrow 0$ . Equally the eigenvectors of  $T(x)$  should lead us to the eigen subspaces  $V_j$  as  $x \rightarrow 0$ . To show how this happens, define the resolvent of  $T_0$ ,  $R_0(\zeta)$  as

$$R_0(\zeta) = (T_0 - \zeta I_q)^{-1} \quad (2.4)$$

where  $\zeta$  is a complex number. By (2.2) we may write

$$R_0(\zeta) = \sum_j (\lambda_j - \zeta)^{-1} P_j \quad (2.5)$$

Observe that  $T_0$  and  $R_0(\zeta)$  commute.

If  $C$  is any contour in the complex plane which does not go through any  $\lambda_j$ , which are points on the real axis, Cauchy's Theorem and (2.5) imply that

$$\frac{1}{2\pi i} \int_C R_0(\zeta) d\zeta = \sum_j P_j \quad (2.6)$$

where the sum is over the projectors  $P_j$  associated with eigenvalues  $\lambda_j$  inside  $C$ . The integral of a matrix is the matrix of integrals. Similarly

$$\frac{1}{2\pi i} \int_C T_0 R_0(\zeta) d\zeta = \sum_{j \in C} \lambda_j P_j \quad (2.7)$$

We observe that the trace of (2.6) gives the sum of the dimensions of the eigen subspaces associated with  $\lambda_j$  within  $C$ . Similarly the trace of (2.7) gives the sum of the eigen values (times their multiplicities) within  $C$ .

We now consider the resolvent of  $T(x)$ .

$$R(x, \zeta) = (T(x) - \zeta I_q)^{-1} = R_0(\zeta) (I_q + x T_1 R_0(\zeta))^{-1} \quad (2.8)$$

If we apply the results of the previous paragraph to  $R(x, \zeta)$ , we will get information about the eigen values  $\lambda(T(x))$  and projectors  $P(T(x))$ , of  $T(x)$ . As  $x \rightarrow 0$ , we would expect the values of  $\lambda(T(x))$  to condense on the eigen values  $\lambda_j$  of  $T_0$ .

To obtain the required formulae, we need to expand (2.8) as a power series. For a  $q \times q$  matrix  $A$ ,

$$(I_q + xA)^{-1} = I_q - xA + x^2 A^2 - \dots \quad (2.9)$$

where the series is absolutely convergent provided  $|x| \|A\| < 1$ , where  $\|A\|$  is a norm of  $A$ . Thus we can say that for  $x$  sufficiently small,

$$(I_q + xA)^{-1} = I_q - xA + O(x^2). \quad (2.10)$$

Applying (2.10) to (2.8), we have, as  $|x| \rightarrow 0$ ,

$$R(x, \zeta) = R_0(\zeta) - x R_0(\zeta) T_1 R_0(\zeta) + O(x^2). \quad (2.11)$$

Consider now the analogue of (2.6) when  $C_j$  is a contour which encloses only the eigen value  $\lambda_j$ . Then

$$\frac{1}{2\pi i} \int_{C_j} R(x, \zeta) d\zeta = \frac{1}{2\pi i} \int_{C_j} R_0(\zeta) d\zeta + \frac{x}{2\pi i} \int_{C_j} R_0(\zeta) T_1 R_0(\zeta) d\zeta + O(x^2) \quad (2.12)$$

The first term on the right hand side (r.h.s.) of (2.12) is  $P_j$ .

To find the second term, we observe that, if we use (2.5) twice,

$$\begin{aligned} R_0(\zeta) T_1 R_0(\zeta) &= \sum_{k=1}^r \sum_{l=1}^r \frac{P_k T_1 P_l}{(\lambda_k - \zeta)(\lambda_l - \zeta)} \\ &= \sum_{k=1}^r \frac{P_k T_1 P_k}{(\lambda_k - \zeta)^2} + \sum_{k < l} \frac{(P_k T_1 P_l + P_l T_1 P_k)}{\lambda_l - \lambda_k} \left( \frac{1}{\lambda_k - \zeta} - \frac{1}{\lambda_l - \zeta} \right) \quad (2.13) \end{aligned}$$

The contour integral of the first term on the r.h.s. of (2.13) is zero.

We get contributions from the second term when  $k$  or  $l$  equal  $j$  and they add to the symmetric matrix

$$\sum_{k \neq j} \frac{P_k T_1 P_j + P_j T_1 P_k}{\lambda_k - \lambda_j} \quad (2.14)$$

Observe, for later use, that this matrix has a zero trace because

$P_j P_k$  is null. Thus

$$\frac{1}{2\pi i} \int_{C_j} R(x, \zeta) d\zeta = P_j + x \sum_{k \neq j} \frac{P_k T_1 P_j + P_j T_1 P_k}{\lambda_j - \lambda_k} + O(x^2) \quad (2.15)$$

is the analogue of (2.6).

The analogue of (2.7) is obtained by integrating  $T(x)R(x, \zeta)$  which may, using (2.1) and (2.11), be written as

$$T(x)R(x, \zeta) = T_0 R_0(\zeta) + x(T_1 R_0(\zeta) - T_0 R_0(\zeta) T_1 R_0(\zeta)) + O(x^2). \quad (2.16)$$

The integral of the first term on the r.h.s. of (2.16) is that in (2.7).

To find the second and third terms we note that

$$T_1 R_0(\zeta) = \sum_{k=1}^r (\lambda_k - \zeta)^{-1} T_1 P_k, \\ T_0 R_0(\zeta) T_1 R_0(\zeta) = \sum_{k=1}^r \frac{\lambda_k P_k T_1 P_k}{(\lambda_k - \zeta)^2} \quad (2.17)$$

$$+ \sum_{k < l} \frac{\lambda_k P_k T_1 P_l + \lambda_l P_l T_1 P_k}{(\lambda_l - \lambda_k)} \left( \frac{1}{\lambda_k - \zeta} - \frac{1}{\lambda_l - \zeta} \right), \quad (2.18)$$

where we have used (2.2) and (2.13). Thus we find that

$$\frac{1}{2\pi i} \int_{C_j} T(x) R(x, \zeta) d\zeta = \lambda_j P_j + x (T_1 P_j) + \sum_{k \neq j} \frac{\lambda_k P_k T_1 P_l + \lambda_l P_l T_1 P_k}{\lambda_j - \lambda_k} \\ + O(x^2). \quad (2.19)$$

Observe that the trace of the second term in the coefficient of  $x$  is zero. (2.19) is the analogue of (2.7).

In the applications we have in mind  $T(x)$  will have  $q$  distinct eigenvalues  $\lambda_1(x), \dots, \lambda_q(x)$  and (orthonormal) eigenvectors  $v_1(x), \dots, v_q(x)$  so that

$$T(x) = \sum_1^q \lambda_i(x) v_i(x) v_i(x)' \quad (2.20)$$

is the spectral form for  $T(x)$ . By using the reasoning that led to (2.6) and (2.7) we may then evaluate the l.h.s.'s of (2.15) and (2.19).

Thus

$$\frac{1}{2\pi i} \int_{C_j} R(x, \zeta) d\zeta = \sum v_i(x) v_i(x)' \quad (2.21)$$

and

$$\frac{1}{2\pi i} \int_{C_j} T(x) R(x, \zeta) d\zeta = \sum \lambda_i(x) v_i(x) v_i(x)' \quad (2.22)$$

where both sums are over  $i$  such that  $\lambda_i(x)$  are points inside the contour  $C_j$ .

Since  $\text{trace } v_i(x) v_i(x)' = v_i'(x) v_i(x) = 1$ , taking the trace of both sides of (2.15) and using (2.21) yields

$$\# \lambda_i(x) \text{ inside } C_j = q_j + O(x^2) \quad (2.23)$$

for any contour  $C_j$  enclosing  $\lambda_j$ . As  $x \rightarrow 0$ , one could use smaller and smaller contours. Hence as  $x \rightarrow 0$ , the eigenvalues of  $T(x)$  form clusters of  $q_j$  roots about  $\lambda_j$  ( $j = 1, \dots, r$ ) which condense upon  $\lambda_j$ . If we do not take the trace of (2.15) and write

$$\hat{P}_j = \sum_{\lambda_i(x) \in C_j} v_i(x) v_i(x)' \quad (2.24)$$

then (2.15) may be written as

$$\hat{P}_j = P_j + x \sum_{k \neq j} \frac{P_k T_1 P_j + P_j T_1 P_k}{\lambda_j - \lambda_k} + O(x^2) \quad (2.25)$$

Taking the trace of (2.19) yields

$$\sum \lambda_i(x) \text{ within } C_j = q_j \lambda_j + x \text{ trace } T_1 P_j + O(x^2) \quad (2.26)$$

so dividing through by  $q_j$  and calling the l.h.s.  $\bar{\lambda}_j$ , the arithmetic mean of the  $j^{\text{th}}$  cluster, we have

$$\bar{\lambda}_j = \lambda_j + \frac{x}{q_j} \text{ trace } T_1 P_j + O(x^2) \quad (2.27)$$

The formulae (2.25) and (2.27) are ideal for statistical applications, as will be seen in the next section. We close this section by observing that there is no problem except complexity in getting higher order approximations - one merely takes higher order terms in (2.10). For example, the coefficient of  $x^2$  in  $R(x_1)$  is  $R_0 T_1 R_0 T_1 R_0$  so using (2.5) and partial fraction expansions the contour integral may be evaluated to give a lengthy formula. One then finds that (2.23) may be improved to

$$\# \lambda_j(x) \text{ inside } C_j = q_j + O(x^3) \quad (2.28)$$

In Watson (1982a) explicit results are given when  $r = 2$ .

### 3. Large sample theory of symmetric cross-product matrices

Let  $x$  be a random vector in  $\mathbb{R}^q$  with components  $x^1, x^2, \dots, x^q$  and suppose that  $E x^i x^j x^k x^l$  exists for all  $i, j, k, l = 1, \dots, q$ . Let  $x'$  denote the transpose of  $x$ . Call  $E x x' = E[x^i x^j] = M$ , a symmetric  $q \times q$  matrix with spectral form

$$M = \sum_j \lambda_j P_j \quad (3.1)$$

If  $x_1, \dots, x_n$  are independent copies of  $x$ , define

$$M_n = n^{-1} \sum_1^n x_i x_i' \quad (3.2)$$

Then  $M_n \rightarrow M$  by the law of large numbers and by the multivariate central limit theorem

$$n^{1/2} (M_n - M) \xrightarrow{d} C. \quad (3.3)$$

The  $q(q+1)/2$  functionally independent elements of the symmetric matrix  $G$  are jointly Gaussian with zero means and a covariance matrix  $V$  whose elements are

$$\mathbb{E} x^i x^j x^k x^l - \mathbb{E}(x^i x^j) \mathbb{E}(x^k x^l), \quad i \leq j, \quad k \leq l. \quad (3.4)$$

To use the results of Section 2, we may write

$$M_n = M + n^{-1/2} \{ n^{1/2} (M_n - M) \} \quad (3.5)$$

instead of

$$T(x) = T_0 + x T_1$$

From (3.3),  $T_1$  corresponds to  $G$ ,  $x$  to  $n^{-1/2}$ , and  $M$  to  $T_0$ . Provided no  $\lambda_j$  in (3.1) is zero, the matrix  $M_n$  will, with probability one, have distinct eigenvalues - Okamoto (1973). If say  $\lambda_1 = 0$ ,  $\mathbb{E}(P_1 x)(P_1 x)'$  is a matrix of zeros so that, taking the trace,  $\mathbb{E} \|P_1 x\|^2 = 0$ . Thus  $P_1 x$  is a null vector and  $M_n$  will have  $q_1$  zero roots and the data will determine the eigen subspace  $V_1$  exactly. This case has little interest so we assume that all the  $\lambda_j > 0$ .

The matrix  $M_n$  will be used to estimate the  $\lambda_j$  and  $P_j$ ,  $j=1, \dots, r$ . Combining (3.5) with (2.24), (2.25) and (2.27), we have the key results:

for  $j = 1, \dots, r$ ,

$$n^{1/2} (\hat{P}_j - P_j) \xrightarrow{d} \sum_{k \neq j} \frac{P_k G P_j + P_j G P_k}{\lambda_j - \lambda_k} \quad (3.6)$$

$$n^{1/2} (\bar{\lambda}_j - \lambda_j) \xrightarrow{d} \frac{1}{q_j} \text{trace } G P_j. \quad (3.7)$$

The r.h.s.'s of (3.6) and (3.7) are linear in the Gaussian matrix  $G$  so that the l.h.s.'s have asymptotically Gaussian distributions with zero means and variances and covariances that depend upon the covariance matrix  $V$  of  $G$ .

(3.7) is univariate and so easy to understand, e.g. it leads to a normal confidence interval for  $\lambda_j$ , although we will see that one will do better with a transformation. (3.6) describes the difference between estimated and true projectors and needs further simplification. Using the Euclidean matrix norm ( $\|A\|^2 = \text{trace } AA'$ ),

$$n \|\hat{P}_j - P_j\|^2 \xrightarrow{d} 2 \sum_{k \neq j} \frac{\text{trace } P_j G P_k G}{(\lambda_j - \lambda_k)^2} \quad (3.8)$$

Again, one might examine the different effects of  $\hat{P}_j$  and  $P_j$  on vectors. For example, if  $v \in V_j$ ,

$$n^{1/2} (\hat{P}_j v - P_j v) \xrightarrow{d} \sum_{k \neq j} \frac{P_k G v}{\lambda_j - \lambda_k} \quad (3.9)$$

so

$$n \|\hat{P}_j v - P_j v\|^2 \xrightarrow{d} \sum_{k \neq j} \frac{v' G P_k G v}{\lambda_j - \lambda_k} \quad (3.10)$$

More fundamentally if  $\hat{V}_j$  is the subspace onto which  $\hat{P}_j$  projects,  $\hat{V}_j$  will be "close" to  $V_j$  if  $\cos \theta = v' \hat{v}$  is always large when  $v \in V_j$  and  $\hat{v} \in \hat{V}_j$ ,  $\|v\| = 1$ ,  $\|\hat{v}\| = 1$ . Thus we should seek the stationary values of  $(P_j u)' (\hat{P}_j v)$ , given  $\|P_j u\| = \|\hat{P}_j v\| = 1$ , i.e., we should consider

$$2u' P_j \hat{P}_j v - \theta u' P_j u - 4v' \hat{P}_j v$$

where  $\theta$  and  $\phi$  are Lagrangian multipliers. Hence

$$\left. \begin{aligned} P_j \hat{P}_j v - \theta P_j u &= 0, \\ \hat{P}_j P_j u - \phi \hat{P}_j v &= 0, \end{aligned} \right\} \quad (3.11)$$

so that

$$\begin{aligned} \theta = \phi &= \text{stationary value of } (P_j u)' (\hat{P}_j v) \\ &= C, \text{ say.} \end{aligned}$$

Hence the equations (3.11) will only have a solution if

$$\begin{vmatrix} -C P_j & P_j \hat{P}_j \\ \hat{P}_j P_j & -C \hat{P}_j \end{vmatrix} = 0 \quad (3.12)$$

This equation for  $C$  may be reduced to

$$\begin{vmatrix} P_j \hat{P}_j P_j - C^2 P_j \end{vmatrix} = 0 \quad (3.13)$$

which has  $q_j$  non-zero roots  $C_i^2$ . If, however, (3.6) is used, one finds eventually that all the  $C_i^2$  are unity. Watson (1982a) deals with the case where  $r = 2$  and shows, by taking the next term in the expansions in Section 2, that  $n(1 - C_i^2)$  have asymptotic distributions. It is conjectured that for any  $r$  the asymptotic joint distribution of  $n(1 - C_1)$ , ...,  $n(1 - C_{q_j})$  is the joint distribution of the non-zero eigenvalues of

$$\sum_{k \neq j} \frac{P_j G P_k G P_j}{(\lambda_j - \lambda_k)^2} \quad (3.14)$$

Some of the above results become easier to understand if we write, since  $I_q = P_1 + \dots + P_r$ ,

$$y_j = P_j x, \quad x = y_1 + \dots + y_r \quad (3.15)$$

One of the reasons results become simpler for the Gaussian is that there  $y_1, \dots, y_r$  are independent. Since  $E x x' = M = \lambda_j P_j$ ,

$$\begin{aligned} E y_k y_l' &= 0, \quad l \neq k, \quad E y_j y_j' = \lambda_j P_j \\ E y_l' y_k &= 0, \quad (l \neq k), \quad E y_j' y_j = \lambda_j q_j \end{aligned} \quad (3.16)$$

Thus (3.7) may be rewritten as

$$\begin{aligned} n^{1/2} (\bar{\lambda}_j - \lambda_j) &\sim \frac{n^{1/2}}{q_j} \text{trace} \left( \frac{1}{n} \sum_{i=1}^n y_{ji} y_{ji}' - \lambda_j P_j \right) \\ &= \frac{n^{1/2}}{q_j} \left( \frac{1}{n} \sum_{i=1}^n y_{ji}' y_{ji} - \lambda_j q_j \right) \end{aligned} \quad (3.17)$$

so that by (3.16) and the Central Limit Theorem

$$\mathcal{L} n^{1/2} (\bar{\lambda}_j - \lambda_j) \longrightarrow G_q(0, \text{var}(y_j' y_j) q_j^{-2}) \quad (3.18)$$

where  $G_q(\mu, \Sigma)$  stands for the Gaussian distribution in  $q$  dimensions with mean vector  $\mu$  and covariance matrix  $\Sigma$ . Similarly (3.6) can be written as

$$n^{1/2} (\hat{P}_j - P_j) \sim n^{-1/2} \sum_{i=1}^n \sum_{k \neq j} \frac{y_{ki} y_{ji}' + y_{ji} y_{ki}'}{\lambda_j - \lambda_k} \quad (3.19)$$

If  $\mathbf{x} = \mathbf{G}_q(0, \mathbf{M})$ ,  $y_1, y_2, \dots, y_r$  are independent and  $\mathbf{L} y_j' y_j \lambda_j^{-1} = x_{q_j}^2$  so that  $\text{var}(y_j' y_j) = \lambda_j^2 2q_j$ . Then (3.18) reads:

$$\mathbf{L} n^{1/2} (\bar{\lambda}_j - \lambda_j) \longrightarrow \mathbf{G}_1(0, 2\lambda_j^2/q_j)$$

Hence

$$\mathbf{L} n^{1/2} (\log(\bar{\lambda}_j/\lambda_j) - 1) \longrightarrow \mathbf{G}_1(0, 2/q_j) \quad (3.20)$$

giving the variance stabilizing transformation. Moreover in this Gaussian case the  $n^{1/2} (\bar{\lambda}_j - \lambda_j)$  or  $n^{1/2} (\log(\bar{\lambda}_j/\lambda_j) - 1)$  are asymptotically independent, a simplifying result which is not true in general. Under no circumstances could it be expected that the  $\hat{p}_j$  would be independent since  $\sum_{j=1}^r \hat{p}_j = I_q$ .

With this introduction, the compact paper by Tyler (1981) may be read for more details on  $\hat{p}_j$ . He also gives tests.

special case of  $r = 2$  and distributions restricted to  $\Omega_q$ , Watson (1982a).

If an additional assumption is made that the distribution of  $\mathbf{x}$  depends only upon  $\|y_1\|, \dots, \|y_r\|$  more results may be derived - see Watson 1982b).

#### 4. Direct approach to large sample theory of cross-product matrices.

The eigenvalues of  $M_n$  are the roots  $\hat{\lambda}$  of

$$|M_n - \lambda I| = |M - \lambda I + \frac{1}{\sqrt{n}} T_1| = 0 \quad (4.1)$$

where, as in Section 3,  $M = \sum_1^r \lambda_j P_j$ ,  $T_1 = \sqrt{n}(M_n - M)$ . Suppose orthonormal eigenvectors are selected to span each of the invariant

subspaces  $V_j$  and arranged as column vectors to form a  $q \times q$  orthogonal matrix  $H$ . Let the first  $q_1$  columns correspond to  $V_1$ , the next  $q_2$  columns to  $V_2$ , etc., and write it in partitioned form

$$H = [H_1, \dots, H_r] \quad (4.2)$$

Then since  $H'H = HH' = I_q$ , we have

$$H_a' H_B = 0(a \neq b), \quad H_a' H_a = I_{q_a},$$

$$H_1 H_1' + \dots + H_r H_r' = I_q, \quad (4.3)$$

$$H_a H_a' = P_a, \quad a = 1, \dots, r,$$

and

$$H'MH = D(\lambda_j I_{q_j}), \quad (4.4)$$

a matrix partitioned so all  $r^2$  submatrices are zero except for the multiples of identity matrices on the diagonal.

If  $H$  is applied to (4.1), it takes the partitioned form.

$$\left| (\lambda_1 - \lambda) I_{q_1} \delta_{ij} + n^{-1/2} H_1' T_1 H_j \right| = 0 \quad (4.5)$$

Since  $n \rightarrow \infty$ , we seek the  $O(1)$  and  $O(n^{-1/2})$  terms only in the expansion of (4.5). Applying the formula

$$\left| \begin{array}{cc} A & C \\ B & D \end{array} \right| = |A| |D - BA^{-1}C|$$

when  $A$  is the leading submatrix of (4.5), it is seen that  $BA^{-1}C$  is  $O(n^{-1})$  and so negligible. Hence we may repeat the procedure to find that equation (4.5) and hence (4.1) is, to this order

$$\sum_{j=1}^r |(\lambda_j - \lambda) I_{q_j} + n^{-1/2} H_j' T_1 H_j| = 0 \quad (4.6)$$

This shows that the eigenvalues of  $M_n$ , for large  $n$ , form clusters about the  $r$  distinct roots  $\lambda_j$  of  $M$ . Expanding the  $j^{\text{th}}$  factor in (4.6) to  $O(n^{-1/2})$ , we only need the product of the diagonal terms and find the equation

$$(\lambda_j - \lambda)^{q_j} (1 + n^{-1/2} \frac{\text{trace } H_j' T_1 H_j}{\lambda_j - \lambda}) = 0 \quad (4.7)$$

Since  $\text{trace } H_j' T_1 H_j = \text{trace } H_j H_j' T_1 = \text{trace } P_j T_1$  by (4.3) the  $q_j$  roots of (4.7) tend to  $\lambda_j$  as  $n \rightarrow \infty$  and the leading terms of the polynomial (degree  $q_j$ ) equation for  $\lambda$  are

$$\lambda^{q_j} - \{q\lambda_j + n^{-1/2} \text{trace } P_j T_1\} \lambda^{q_j-1} + \dots = 0 \quad (4.8)$$

so that if the roots of this equation are denoted by  $\hat{\lambda}$ ,

$$\sum \hat{\lambda} = q\lambda_j + n^{-1/2} \text{trace } P_j T_1, \quad (4.9)$$

as we found in (3.27). But one cannot expect to obtain the roots in the cluster for  $\lambda_j$  from (4.7) (it gives them to be  $\lambda_j$  ( $q-1$  times),  $\lambda_j + n^{-1/2} \text{trace } P_j T_1$  (once)) because when  $\lambda$  is within  $n^{-1/2}$  of  $\lambda$  all the terms in the matrix in (4.6) are of order  $n^{-1/2}$ . However, (4.8) does give the correct coefficient for  $\lambda^{q_j-1}$  in (4.6).

Since the eigenvalues of  $M_n$  will in general be distinct, the approximations made above are inadequate to discuss e.g. the joint distribution of the eigenvalues in a cluster.

The following direct derivation of the analogue of (2.25) or (3.6) is harder to justify. Write

$$\hat{P}_j = P_j + n^{-1/2} \Delta, \Delta = n^{1/2} (\hat{P}_j - P_j) \quad (4.10)$$

and, because the roots in the cluster are within  $n^{-1}$  of  $\lambda_j$ , set

$$M_n \hat{P}_j = (\lambda_j + n^{-1/2} \delta) \hat{P}_j \quad (4.11)$$

i.e.

$$(M + n^{-1/2} T_1) (P_j + n^{-1/2} \Delta) = (\lambda_j + n^{-1/2} \delta) (P_j + n^{-1/2} \Delta)$$

so that the terms in  $n^{-1/2}$  yield the equation

$$T_1 P_j + M \Delta = \lambda_j \Delta + \delta P_j$$

or

$$(M - \lambda_j I) \Delta = -T_1 P_j + \delta P_j \quad (4.12)$$

But  $M - \lambda_j I = \sum_{k \neq j} (\lambda_k - \lambda_j) P_k$  so that we could replace  $\Delta$  by  $\Delta - P_j X$  and still satisfy (4.12). Thus (4.12) is solved by multiplying (4.12) by  $\sum (\lambda_k - \lambda_j)^{-1} P_k$  and adding  $P_j X$  so that

$$\Delta = \sum_{k \neq j} (\lambda_j - \lambda_k)^{-1} P_k T_1 P_j + P_j X.$$

However, from (4.10) we see that  $\Delta$  must be symmetric and this determines  $X$ . Thus

$$\Delta = n^{1/2}(\hat{P}_j - P_j) = \sum_{k \neq j} \frac{P_k^T P_j + P_j^T P_k}{\lambda_j - \lambda_k} \quad (4.13)$$

which is the desired result. However, without the results of Section 3, (4.10) and (4.11) are merely intuitions.

### 5. Additional Remarks

(i) Suppose  $(x_i, y_i)$  for  $i = 1, \dots, n$  are independent copies of a pair of random vectors  $(x, y)$ ,  $x \in \mathbb{R}^q$ ,  $y \in \mathbb{R}^p$ . Define the estimator of  $N = Exy'$

$$N_n = n^{-1} \sum_1^n x_i y_i' \quad (5.1)$$

and assume that the Central Limit Theorem holds so that

$$n^{1/2} (N_n - N) \xrightarrow{d} F \quad (5.2)$$

One may wish to estimate the singular values of  $N$  so one would find the non-zero eigenvalues of  $N_n N_n'$  or  $N_n' N_n$  whichever is the smaller. But using (5.2),

$$N_n' N_n \sim N' N + n^{-1/2} (F' N + N' F) \quad (5.3)$$

so that the previous theory is applicable.

(ii) Suppose that  $x_1, \dots, x_n$  is a sample from one  $q$  dimensional distribution,  $x_1^*, \dots, x_n^*$  a sample from another distribution in  $\mathbb{R}^q$  and let  $M_n = n^{-1} \sum x_i x_i'$ ,  $M_n^* = n^{-1} \sum x_i^* x_i^{*'}$ . Then we often need to study the solutions of

$$(M_n - \lambda M_n^*)v = 0 \quad (5.4)$$

Anderson (1958) gives examples and calls  $\lambda$  and  $v$  the eigen values and vectors of  $M_n$  in the metric of  $M_m$ . To study them in large samples we suppose that the Central Limit Theorem applies in both cases so that as  $n, m \rightarrow \infty$

$$\left. \begin{aligned} M_n &\sim M + n^{-1/2} G, \\ M_m^* &\sim M^* + m^{-1/2} G^*. \end{aligned} \right\} \quad (5.5)$$

The eigenvalues are those of  $M_m^{*-1/2} M_n M_m^{*-1/2}$  which by (5.5) are those of

$$\begin{aligned} & M_m^{-1/2} (I_q - \frac{n}{2} G^* M_m^{-1}) (M + n^{-1/2} G) (I_q - \frac{m}{2} M_m^{-1} G^* M_m^{-1/2}) \\ &= M_m^{-1/2} M M_m^{-1/2} + M_m^{-1/2} G M_m^{-1/2} \\ &= \frac{n}{2} M_m^{-1/2} G^* M_m^{-1} M M_m^{-1/2} \\ &= \frac{n}{2} M_m^{-1/2} M M_m^{-1} G^* M_m^{-1/2} \end{aligned} \quad (5.6)$$

If we set  $n = \alpha l$ ,  $m = \beta l$  with  $\alpha, \beta > 0$  and  $l \rightarrow \infty$  (5.6) has the form of a symmetric fixed matrix plus  $l^{-1/2}$  times a symmetric Gaussian matrix so that the earlier theory is applicable.

References

Anderson, T.W. (1958), Introduction to Multivariate Analysis,  
John Wiley & Sons, New York.

Anderson, T.W. (1963), Asymptotic Theory for Principal Components,  
Ann.Math.Stat. 34, 122-148.

Davis, A.W. (1977), Asymptotic Theory for Principal Components,  
Austral.J.Statist. 19 (3), 206-212.

Kim, K.M. (1978), Orientation Shift Model on the Sphere.  
Ph.D. Thesis, Univ. of California, Berkeley.

Kato, T. (1980), Perturbation Theory for Linear Operators,  
2nd Edition, Springer-Verlag, New York.

Muirhead, Robb J. (1982), Aspects of Multivariate Statistical Theory,  
John Wiley & Sons, New York.

Tyler, D.E. (1979), Redundancy Analysis and Associated Asymptotic  
Distribution Theory, Ph.D. Thesis, Princeton  
University.

Tyler, D.E. (1981), Asymptotic Inference for Eigenvectors,  
Ann.Statistics 9 (4), 725-736.

Watson, G.S. (1982a), Large Sample Theory for Distributions on the  
Hypersphere with Rotational Symmetries.  
Technical Report, Dept. of Statistics,  
Princeton University.

Watson, G.S. (1982b), Distributions in  $\mathbb{R}^q$  with Rotational Symmetries.  
Technical Report, Dept. of Statistics,  
Princeton University.

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